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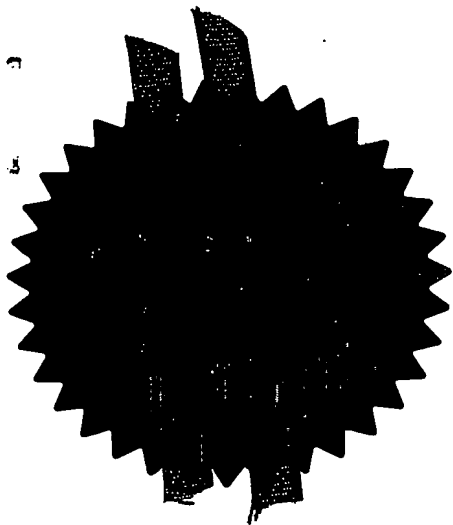
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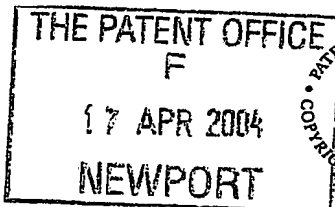
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4169546001

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IMAGE RECOGNITION

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Claim(s)

Abstract

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Stanley S.

STANLEYS

15 April 2004

Date

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## IMAGE RECOGNITION

This invention relates to the recognition of images, and is concerned, particularly although not exclusively, with the recognition of natural images.

By "natural image" is meant an image of an object that occurs naturally –  
5 for example, an optical image such as a photograph, as well as images of other  
wavelengths – such as x-ray and infra-red, by way of example. The natural image  
may be recorded and/or subsequently processed by digital means, but is in contrast  
to an image – or image data – that is generated or synthesised by computer or other  
artificial means.

10 The recognition of natural images can be desirable for many reasons. For  
example, distinctive landscapes and buildings can be recognised, to assist in the  
identification of geographical locations. The recognition of human faces can be  
useful for identification and security purposes. The recognition of valuable animals  
such as racehorses may be very useful for identification purposes.

15 In this specification, we present in preferred embodiments of the invention  
a new approach to face recognition.

Preferred embodiments of the present invention may be combined with  
techniques disclosed in our pending application GB0323662.7, a copy of the  
specification and drawings of which is attached, and to which the reader's attention  
20 is directed.

















Previous work [1,2,3,4,5,6,7,8] has shown that the use of 3D face models  
is able to overcome some of the problems associated with 2D face recognition.  
Firstly, by relying on geometric shape, rather than colour and texture information,  
systems become invariant to lighting conditions. Secondly, the ability to rotate a  
25 facial structure in three-dimensional space, allowing for compensation of  
variations in pose, aids those methods requiring alignment prior to recognition.

Finally, the additional discriminatory information available in the facial surface structure, not available from two-dimensional images, provides additional cues for recognition.

It has also been shown that the use of pre-processing techniques applied  
5 prior to training and recognition, in which distinguishing features are made more explicit, environmental effects are normalised and noise content is reduced, can significantly improve recognition accuracy [1, 9, 10]. However, the focus of previous research has been on identifying the optimum surface representation, with little regard for the advantages offered by each individual surface  
10 representation. We suggest that different surface representations may be specifically suited to different capture conditions or certain facial characteristics, despite having a general weakness for overall recognition. For example, curvature representations may aid recognition by making the system more robust to inaccuracies in 3D orientation, yet be highly sensitive to noise. Another  
15 representation may enhance nose shape, but loose the relative positions of facial features. The benefit of using multiple eigenspaces has previously been examined by Pentland et al [11], in which specialist eigenspaces were constructed for various facial orientations and local facial regions, from which cumulative match scores were able to reduce error rates. Our approach differs in that we extract and  
20 combine individual dimensions, creating a single unified surface space. This approach has been shown to work effectively when applied to two-dimensional images by Heseltine et al [12].

Here we analyse and evaluate a range of 3D face recognition systems, each utilising a different surface representation of the facial structure, in an  
25 attempt to identify and isolate the advantages offered by each representation. Focusing on the fishersurface method of face recognition, we propose a means of selecting and extracting components from the surface subspace produced by each system, such that they may be combined into a unified surface space.

Prior to training and testing, 3D face models are converted into one of the following surface representations. This is done by firstly orientating the 3D face model to face directly forwards, then projecting into a depth map. The surfaces in the table below are then derived by pre-processing of depth maps.

Horizontal Derivative		Vertical Derivative		Horizontal Derivative 2		Vertical Derivative 2	
	-1 1		-1 1		-1 0 0 0 1		-1 0 0 0 1
Applies the 2x1 kernel to compute the horizontal derivative		Applies the 1x2 kernel to compute the vertical derivative		Horizontal gradient over a greater horizontal distance		Vertical gradient over a greater vertical distance	
Laplacian		Sobel X		Sobel Y		Sobel Magnitude	
	0 1 0 1 -4 1 0 1 0		-1 0 1 -2 0 2 -1 0 1		1 2 1 0 0 0 -1 -2 -1		
An isotropic measure of the second spatial derivative		Application of the horizontal sobel derivative filter		Application of the vertical sobel derivative filter		The magnitude of Sobel X and Y combined.	
Horizontal Curvature		Vertical Curvature		Curvature Magnitude		Curve Type	
							
Applies sobel X twice to calculate the second horizontal derivative		Applies sobel Y twice to calculate the second vertical derivative		The magnitude of the vertical and horizontal curvatures		Segmentation of the surface into 8 discrete curvature types	
Min Curvature		Max Curvature		Abs Min Curvature		Abs Max Curvature	
							
The minimum of the horizontal and vertical curvature values		The maximum of the horizontal and vertical curvature values		The minimum of the absolute horizontal and vertical curvatures		The maximum of the absolute horizontal and vertical curvatures	

We give here a brief explanation of the fisherface method of face recognition, as described by Belhumeur et al [13] and how it is applied to three-

dimensional face surfaces, termed the fishersurface method. We apply both principal component analysis and linear discriminant analysis to surface representations of 3D face models, producing a subspace projection matrix, similar to that used in the eigenface [11] and eigensurface [1] methods. However, the fishersurface method is able to take advantage of 'within-class' information, minimising variation between multiple face models of the same person, yet still maximising class separation. To accomplish this, we expand the training set to contain multiple examples of each subject, describing the variance of a person's face structure (due to influences such as facial expression and head orientation), from one face model to another, as shown in equation 1.

$$\text{Training Set} = \underbrace{\{\Gamma_1, \Gamma_2, \Gamma_3, \Gamma_4, \Gamma_5, \Gamma_6, \Gamma_7, \Gamma_8, \Gamma_9, \Gamma_{10}, \Gamma_{11}, \Gamma_{12}, \Gamma_{13}, \dots, \Gamma_M\}}_{X_1} \underbrace{\quad}_{X_2} \underbrace{\quad}_{X_3} \underbrace{\quad}_{X_4} \underbrace{\quad}_{X_c} \quad (1)$$

Where  $\Gamma_i$  is a facial surface and the training set is partitioned into  $c$  classes, such that each surface in each class  $X_i$  is of the same person and no single person is present in more than one class. We continue by computing three scatter matrices, representing the within-class ( $S_w$ ), between-class ( $S_B$ ) and total ( $S_T$ ) distribution of the training set throughout surface space, shown in equation 2.

$$S_T = \sum_{i=1}^M (\Gamma_i - \Psi)(\Gamma_i - \Psi)^T \quad S_B = \sum_{i=1}^c N_i (\Psi_i - \Psi)(\Psi_i - \Psi)^T \quad S_w = \sum_{i=1}^c \sum_{\Gamma_i \in X_i} (\Gamma_i - \Psi_i)(\Gamma_i - \Psi_i)^T \quad (2)$$

Where  $\Psi = \frac{1}{N} \sum_{i=1}^M \Gamma_i$  is the average surface of the entire training set, and  $\Psi_i = \frac{1}{|X_i|} \sum_{\Gamma_i \in X_i} \Gamma_i$ , the average of class  $X_i$ . By performing PCA using the total scatter matrix  $S_T$ , and taking the top  $M-c$  principal components, we produce a projection matrix  $U_{pca}$ , used to reduce dimensionality of the within-class scatter matrix, ensuring it is non-singular before computing the top  $c-1$  (in this case 49) eigenvectors of the reduced scatter matrix ratio,  $U_{fd}$  as shown in equation 3.

$$U_{fid} = \arg \max_U \left( \frac{|U^T U_{pca}^T S_B U_{pca} U|}{|U^T U_{pca}^T S_W U_{pca} U|} \right) \quad (3)$$

Finally, the matrix  $U_{ff}$  is calculated as shown in equation 4, such that it may project a face surface into a reduced surface space of  $c-1$  dimensions, in which the between-class scatter is maximised for all  $c$  classes, while the within-class scatter is minimised for each class  $X_i$ .

$$U_{ff} = U_{fid} U_{pca} \quad (4)$$

Once the matrix  $U_{ff}$  has been constructed it is used in much the same way as the projection matrix in the eigenface and eigensurface systems, reducing dimensionality of face surface vectors from 5330 to just 49 ( $c-1$ ) elements. Again, like the eigenface system, the components of the projection matrix can be viewed as images, as shown in figure X for the depth map surface space.

Once surface space has been defined, we project a facial surface into surface space by a simple matrix multiplication using the matrix  $U_{ff}$ , as shown in equation 5.

$$\omega_k = u_k^T (\Gamma - \Psi) \quad \text{for } k = 1 \dots c-1. \quad (5)$$

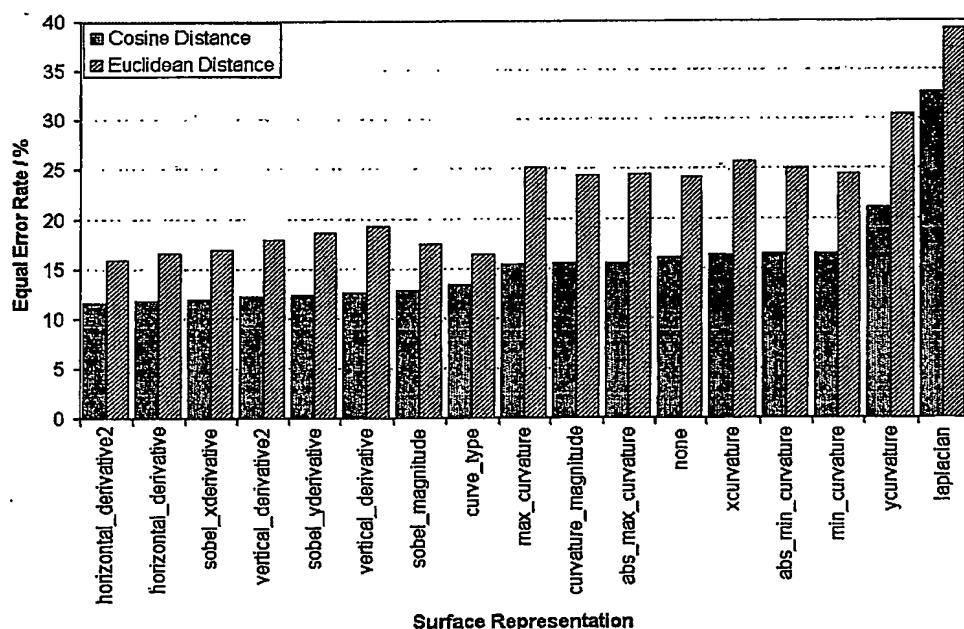
where  $u_k$  is the  $k$ th eigenvector and  $\omega_k$  is the  $k$ th weight in the vector  $\Omega^T = [\omega_1, \omega_2, \omega_3, \dots, \omega_M]$ . The  $c-1$  coefficients represent the contribution of each respective fishersurface to the original facial surface structure. The vector  $\Omega$  is taken as the 'face-key' representing a person's facial structure in reduced dimensionality surface space and compared using either euclidean or cosine distance metrics as shown in equation 6.

$$d_{euclidean} = \|\Omega_a - \Omega_b\| \quad d_{cosine} = 1 - \frac{\Omega_a^T \Omega_b}{\|\Omega_a\| \|\Omega_b\|} \quad (6)$$



An acceptance (the two facial surfaces match) or rejection (the two surfaces do not match) is determined by applying a threshold to the distance calculated. Any comparison producing a distance value below the threshold is considered an acceptance.

Here we analyse the surface spaces produced when various facial surface representations are used with the fishersurface method. We begin by providing results showing the range of error rates produced when using various surface representations. The figure below clearly shows that the choice of surface representation has a significant effect on the effectiveness of the fishersurface method, with horizontal gradient representations providing the lowest equal error rates (EER, the error when FAR equals FRR).



However, the superiority of the horizontal gradient representations does not suggest that the vertical gradient and curvature representations are of no use whatsoever and although the discriminatory information provided by these

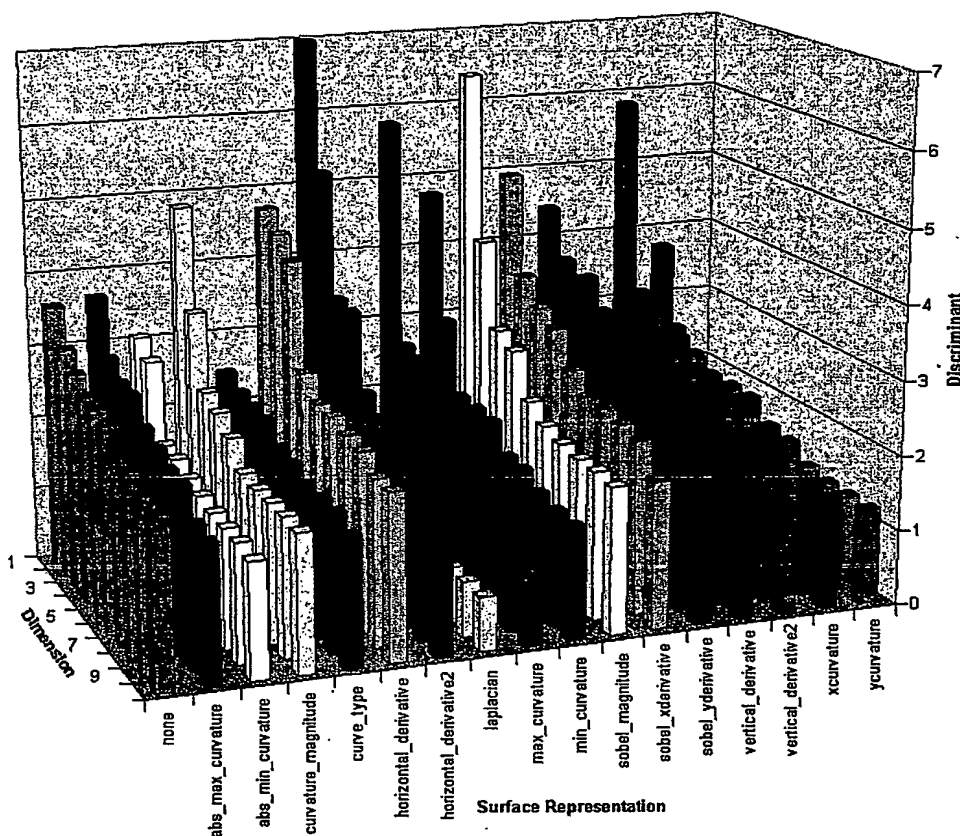
representations may not be as robust and distinguishing, that is not to say they wouldn't make a positive contribution to the information already available in the horizontal gradient representations. We now carry out further investigation into the discriminating ability of each surface space by applying Fisher's Linear Discriminant (FLD), as used by Gordon [3] to analyse 3D face features, to individual components (single dimensions) of each surface space. Focusing on a single face space dimension we calculate the discriminant  $d$ , describing the discriminating power of that dimension, between  $c$  people.

$$d = \frac{\sum_{i=1}^c (m_i - m)^2}{\sum_{i=1}^c \frac{1}{|\Phi_i|} \sum_{x \in \Phi_i} (x - m_i)^2}$$

10

Where  $m$  is the mean value of that dimension in the face-keys,  $m_i$  the within-class mean of class  $i$  and  $\Phi_i$  the set of vector elements taken from the face-keys of class  $i$ . Applying the above equation to the assortment of surface space systems generated using each facial surface representation, we see a wide range of discriminant values describing the distinguishing ability of each individual dimension, as shown below for the top ten most discriminating dimensions for each surface representation.

15



It is clear that although some surface representations do not perform well in the face recognition tests, producing high EERs (for example min\_curvature), some of their face-key components do contain highly discriminatory information. We hypothesise that the reason for these highly discriminating anomalies, in an otherwise ineffective subspace, is that a certain surface representation may be particularly suited to a single discriminating factor, such as nose shape or jaw structure, but is not effective when used as a more general classifier. Therefore, if we were able to isolate these few useful qualities from the more specialised subspaces, they could be used to make a positive contribution to a generally more effective surface space, reducing error rates further.

Here we describe how the analysis methods discussed in above are used to combine multiple face recognition systems. Firstly, we need to address the problem of prioritising surface space dimensions. Because the average magnitude and deviation of face-key vectors from a range of systems are likely to differ by

some orders of magnitude, certain dimensions will have a greater influence than others, even if the discriminating abilities are evenly matched. To compensate for this effect, we normalise moments by dividing each face-key element by its within-class standard deviation. However, in normalising these dimensions we have also  
5 removed any prioritisation, such that all face space components are considered equal. Although not a problem when applied to a single surface space, when combining multiple dimensions we would ideally wish to give greater precedence to the more reliable components. Otherwise the situation is likely to arise when a large number of less discriminating (but still useful) dimensions begin to outweigh  
10 the fewer more discriminating ones, diminishing their influence on the verification operation and hence increasing error rates. We showed how FLD could be used to measure the discriminating ability of a single dimension from any given face space. We now apply this discriminant value  $d$  as a weighting for each face space dimension, prioritising those dimensions with the highest discriminating ability.

15 With this weighting scheme applied to all face-keys produced by each system, we can begin to combine dimensions into a single unified surface space. In order to combine multiple dimensions from a range of surface spaces, we require some criterion to decide which dimensions to combine. It is not enough to rely purely on the discriminant value itself, as this only gives us an indication of  
20 the discriminating ability of that dimension alone, without any indication of whether the inclusion of this dimension would benefit the existing set of dimensions. If an existing surface space already provides a certain amount of discriminatory ability, it would be of little benefit (or could even be detrimental) if we were to introduce an additional dimension describing a feature already present  
25 within the existing set.

Previous investigations [12] have used FLD, applied to a combined eigenspace in order to predict its effectiveness when used for recognition. Additional dimensions are then introduced if they result in a greater discriminant value. Such a method has been shown to produce an 2D eigenspace combination

able to achieve significantly lower error rates in 2D face recognition, although Heseltine et al also note that using the EER would likely provide better results, although processing time would be extremely long. However, with a more efficient combination algorithm we now take that approach, such that the criterion required  
5 for a new dimension to be introduced to an existing surface space is a resultant increase in the EER.

*Combined surface space* = first dimension of current optimum system

Calculate *EER* of *combined surface space*

For each surface space system:

For each *dimension* of surface space:

Concatenate new *dimension* onto *combined surface space*

Calculate *EER* of *combined surface space*

If *EER* has not increased:

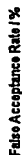
Remove new *dimension* from *combined surface space*

Save *combined surface space* ready for evaluation

The figure below shows which dimensions from which surface space were selected using the above algorithm, for inclusion in two combined systems: one  
10 using the euclidean distance metric and the other using the cosine distance metric.

— 25 —

5



The error curves above show the results obtained when the optimum single fishersurface system and combined fishersurface system are applied to test set A (used to construct the combined system), test set B (the unseen test set) and  
5 the full test set (all images from sets A and B) using the cosine and euclidean distance metrics. We see that the combined systems (dashed lines) do produce lower error rates than the single systems for both the cosine and Euclidean distance measure. The optimum system can be seen as the fishersurface combination using the cosine distance, producing an EER of 7.2% 9.3% and 8.2%  
10 for test set A, B and A and B respectively.

In one aspect, embodiments of the invention as described above apply the use of a fisherface method to the recognition of images, preferably natural images, preferably faces, and preferably human faces.

In another aspect, one or more pre-processing methods are applied prior  
15 to use of a fisherface method.

In another aspect, pre-processed data is combined prior to use of a fisherface method.

As indicated above, methods as disclosed herein may be combined with advantage with those disclosed in our prior, pending application GB0323662.7.

20 In this specification, the verb "comprise" has its normal dictionary meaning, to denote non-exclusive inclusion. That is, use of the word "comprise" (or any of its derivatives) to include one feature or more, does not exclude the possibility of also including further features.

The reader's attention is directed to all and any priority documents  
25 identified in connection with this application and to all and any papers and

documents which are filed concurrently with or previous to this specification in connection with this application and which are open to public inspection with this specification, and the contents of all such papers and documents are incorporated herein by reference.

5 All of the features disclosed in this specification, and/or all of the steps of any method or process so disclosed, may be combined in any combination, except combinations where at least some of such features and/or steps are mutually exclusive.

10 Each feature disclosed in this specification may be replaced by alternative features serving the same, equivalent or similar purpose, unless expressly stated otherwise. Thus, unless expressly stated otherwise, each feature disclosed is one example only of a generic series of equivalent or similar features.

The invention is not restricted to the details of the foregoing embodiment(s). The invention extends to any novel one, or any novel  
15 combination, of the features disclosed in this specification, or to any novel one, or any novel combination, of the steps of any method or process so disclosed.

#### References:

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- 20 13. Belhumeur, J. Hespanha, D. Kriegman, "Eigenfaces vs. Fisherfaces: Face Recognition using class specific linear projection", *Proc. of the European Conference on Computer Vision*, pp. 45-58, 1996.











01	02	03	04	05
				
Front neutral expression	Facing 45° up	Facing 45° down	Happy expression	Eyes closed
06	07	08	09	10
				
Angry expression	2 <sup>nd</sup> Neutral	Eyebrows raised	3 <sup>rd</sup> Neutral	Farther from camera

Fig. 1. Example face models taken from a 3D face database



Fig. 2. Orientation of a raw 3D face model (*left*) to a frontal pose (*middle*) and facial surface depth map (*right*)



Fig. 3. Average depth map (*left most*) and first eight eigensurfaces

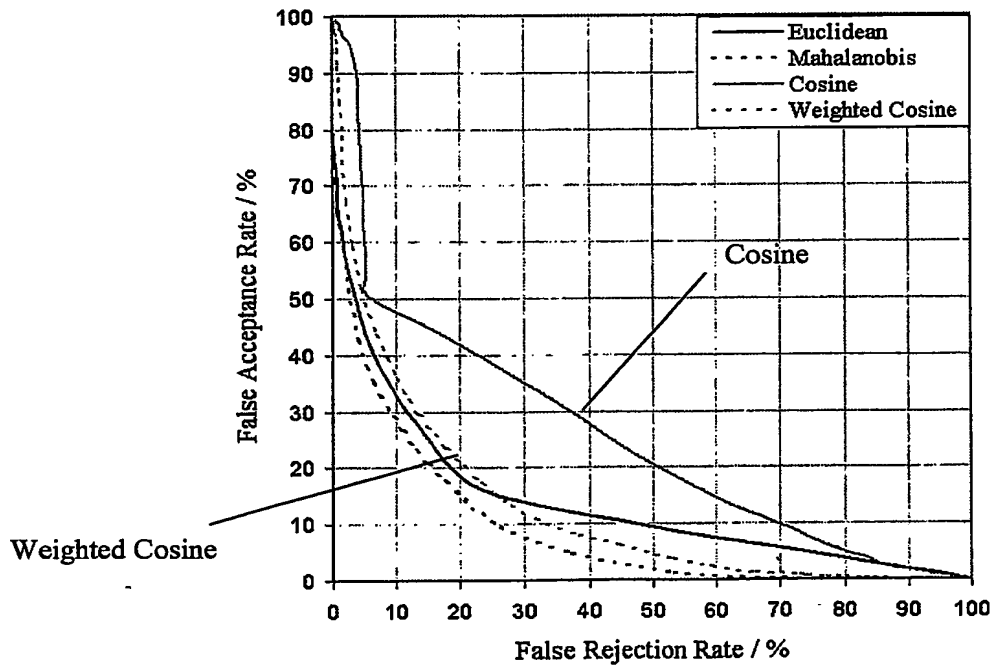


Fig. 4. Baseline 3D face recognition systems using facial surface depth maps and a range of distance metrics

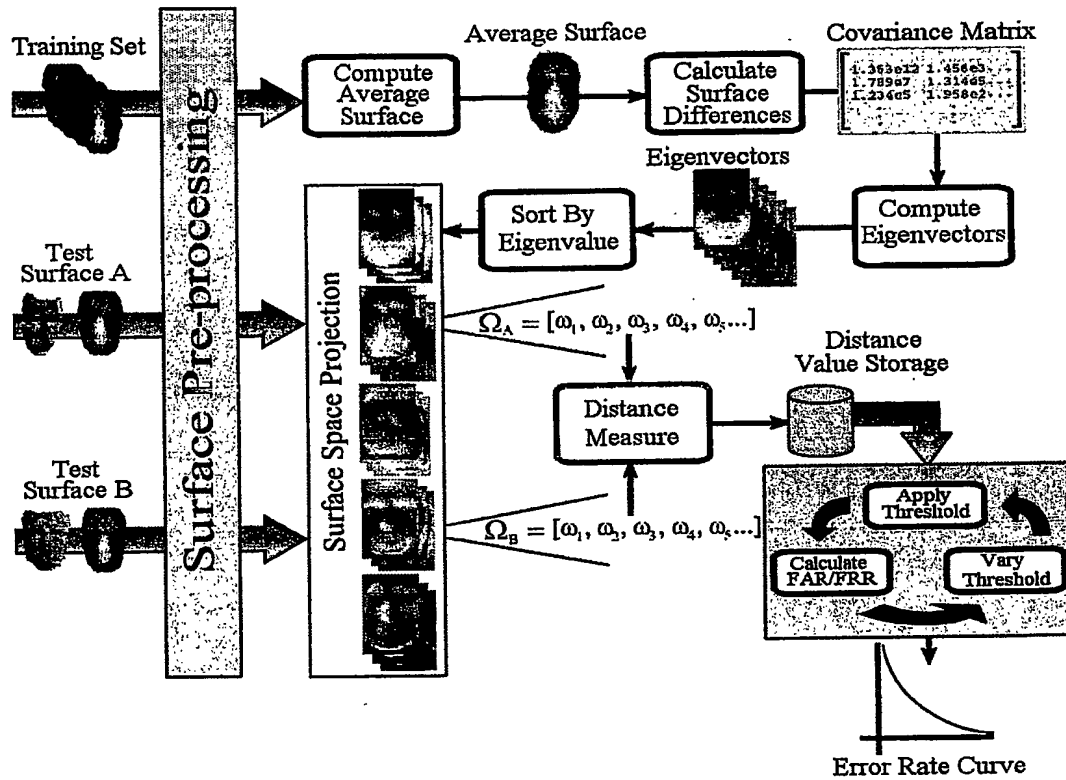
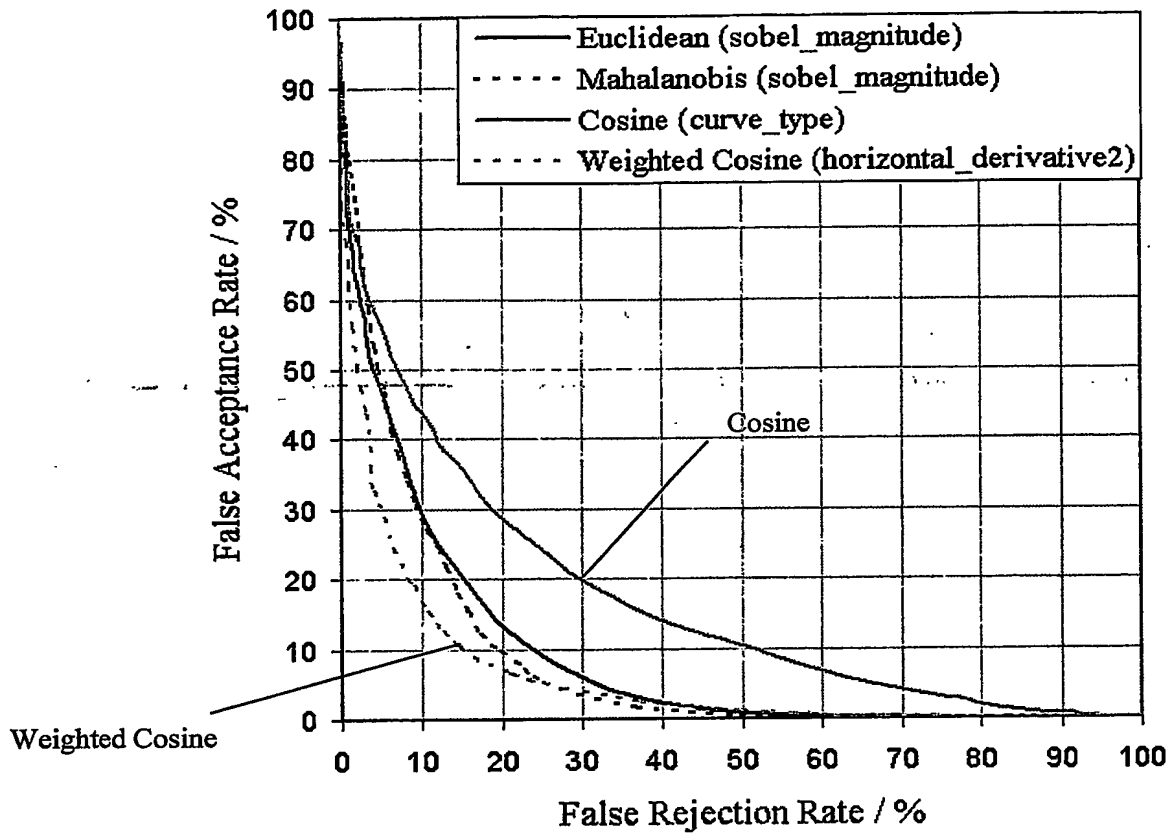


Fig. 5. Diagram of verification test procedure



**Fig. 6.** Error rates of 3D face recognition systems using optimum surface representations and distance metrics.

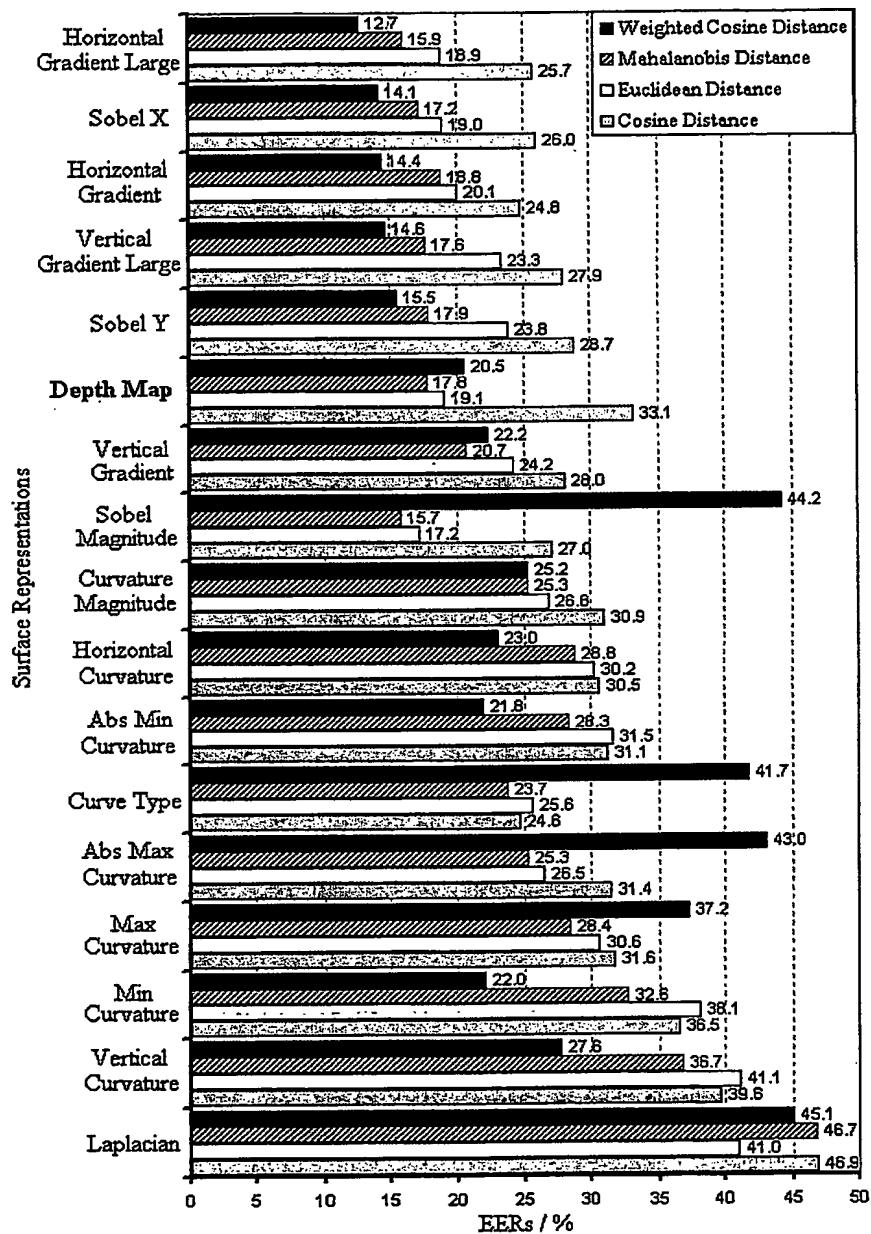


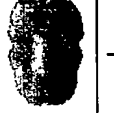















Fig. 7. Equal error rates of 3D face recognition systems using a variety of surface representations and distance metrics

Horizontal Gradient		Vertical Gradient		Horizontal Gradient Large		Vertical Gradient Large	
	-1 1		-1 1		-1 0 0 0 1		-1 0 0 0 1
Applies the 2x1 kernel to compute the horizontal derivative		Applies the 1x2 kernel to compute the vertical derivative		Horizontal gradient calculated over a greater horizontal distance		Vertical gradient calculated over a greater vertical distance	
Laplacian		Sobel X		Sobel Y		Sobel Magnitude	
	0 1 0 1 -4 1 0 1 0		-1 0 1 -2 0 2 -1 0 1		1 2 1 0 0 0 -1 -2 -1		
An isotropic measure of the second spatial derivative		Application of the sobel derivative filter in the horizontal direction		Application of the sobel derivative filter in the vertical direction		The magnitude of the X and Y sobel derivatives	
Horizontal Curvature		Vertical Curvature		Curvature Magnitude		Curve Type	
							
Applies the sobel X kernel twice to calculate the second horizontal derivative		Applies the sobel Y kernel twice to calculate the second vertical derivative		The magnitude of the vertical and horizontal curvatures		Segmentation of the surface into 8 discrete curvature types	
Min Curvature		Max Curvature		Abs Min Curvature		Abs Max Curvature	
							
The minimum of the horizontal and vertical curvature values		The maximum of the horizontal and vertical curvature values		The minimum of the absolute horizontal and vertical curvatures		The maximum of the absolute horizontal and vertical curvatures	

**Figure 8.** Brief descriptions of surface representations with the convolution kernels used.

*son*  
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